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Machine Learning based Framework for the Early Detection and Diagnosis of Glaucoma

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Glaucoma, a leading cause of irreversible blindness, often remains undetected in its early stages due to a lack of symptoms and the limitations of traditional diagnostic methods, such as manual cup-to-disc ratio (CDR) calculation. Accurate early detection is critical to prevent permanent vision loss, yet conventional approaches are time-consuming and prone to inaccuracies. This study introduces a hybrid machine learning framework that combines Convolutional Neural Networks (CNN) and Support Vector Machines (SVM) to address these challenges. Retinal fundus images are preprocessed and segmented to isolate the optic disc and optic cup, enabling precise CDR computation. The CNN extracts high-level features, which are then classified by the SVM into normal or glaucomatous conditions. Data augmentation and transfer learning enhance the model's robustness, addressing the challenges posed by limited training datasets and overfitting. This framework offers a scalable and reliable solution for automated glaucoma detection, facilitating early intervention and improved clinical outcomes. With its high accuracy and adaptability, the proposed approach has significant potential for real-world applications in ophthalmology, paving the way for more efficient and accessible glaucoma screening systems.

Keywords: CNN, SVM, Glaucoma, CDR.

1. Introduction

Glaucoma, a progressive optic neuropathy and one of the leading causes of irreversible blindness worldwide, presents significant challenges in early detection and diagnosis. The disease is primarily caused by elevated intraocular pressure (IOP), which leads to optic nerve head (ONH) damage and vision loss. Traditionally, glaucoma diagnosis has relied on methods such as manual cup-to-disc ratio (CDR) calculation, tonometry, and perimetry. These conventional approaches are time-consuming, require skilled practitioners, and often fail to identify the disease at its earliest stages, when intervention is most effective [11]. Early-stage glaucoma is typically asymptomatic, leaving many cases undetected until irreversible damage occurs (Figure 1).

Figure 1: Illustration of normal vision, early and advanced stage of glaucoma

Glaucoma is a progressive disease that damages the optic nerve head, leading to irreversible vision loss and blindness if left untreated. Originating from the optic disc (OD), the optic nerve is adversely impacted by elevated intraocular pressure, which alters the size and shape of the optic cup (OC), an inner segment of the optic disc. Figure 2 shows the normal and vision of glaucoma patients. The cup-to-disc ratio (CDR), a critical diagnostic indicator, is typically 0.3 in healthy individuals. Manual detection of CDR, involving the marking and measurement of the OD and OC areas from retinal fundus images, is time-consuming and often prone to inaccuracies [12]. To address these limitations, the proposed work employs an Artifact Convolutional Neural Network (ACNN) to classify retinal fundus images as normal or glaucomatous. The methodology involves preprocessing to remove noise, segmentation to isolate the OD and OC areas, and feature extraction to compute the CDR for classification. Utilizing the Drion DB dataset for training and testing, this approach automates and enhances the accuracy of glaucoma detection. With glaucoma being the second leading cause of blindness globally affecting around 79 million people worldwide, including 11.9 million in India early diagnosis is vital, particularly for individuals over 60 years of age, who are often unaware of the disease until significant vision loss occurs. Periodic screening and advanced diagnostic techniques like ACNN can enable timely intervention, slowing disease progression and preserving vision [13-14].

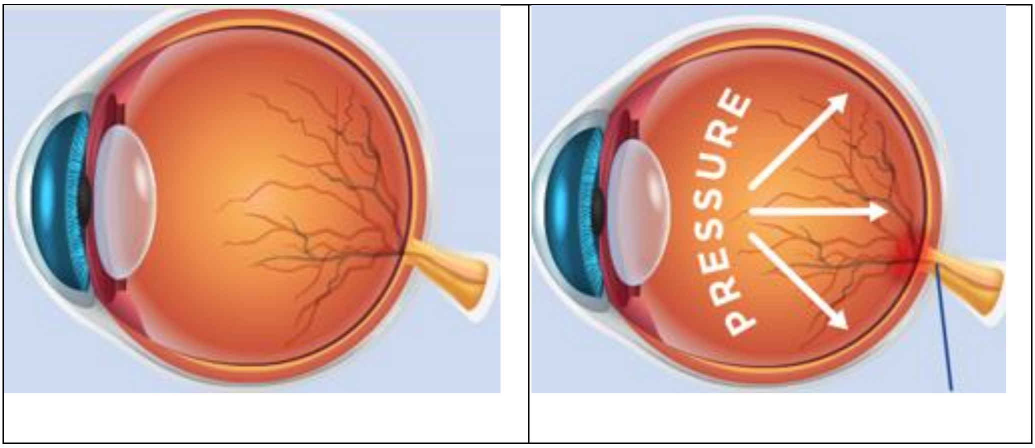

Figure 2: Normal and Glaucoma eye vision

Recent advancements in medical imaging and machine learning (ML) have significantly enhanced the accuracy and efficiency of glaucoma detection. Deep learning techniques, such as Convolutional Neural Networks (CNN), have shown great promise in processing retinal fundus images for optic disc and optic cup segmentation, enabling precise CDR calculation. These automated methods outperform traditional approaches by reducing the need for manual intervention and offering scalability. Additionally, hybrid models, such as CNN integrated with Support Vector Machines (SVM), have emerged as robust solutions, combining the feature extraction capabilities of deep learning with the classification accuracy of machine learning [15]. These models address common issues like overfitting and limited dataset size, improving diagnostic performance across diverse populations.

Looking to the future, the integration of advanced technologies such as transfer learning, explainable AI, and multimodal data fusion holds the potential to revolutionize glaucoma screening and management. AI-powered systems that combine retinal imaging with patient demographics and medical history can provide a holistic approach to diagnosis. Furthermore, the development of portable and cost-effective AI devices could enable large-scale screening programs in low-resource settings, ensuring early detection for underserved populations [16]. With continuous advancements in computational power and access to larger, annotated datasets, machine learning frameworks are poised to play a critical role in making glaucoma detection faster, more accurate, and accessible, ultimately reducing the global burden of blindness.

2. REVIEW OF LITERATURE

Glaucoma detection has been extensively studied with various methods aimed at segmenting the optic disc (OD) and optic cup (OC) to calculate the Cup-to-Disc Ratio (CDR). One study proposed using manual thresholding, region of interest (ROI)-based segmentation, and component analysis, where the segmentation of OD relied on pixel intensity and color component analysis, achieving higher accuracy under high-contrast conditions. However, this approach suffered from imprecise boundary detection [17]. A classification method employing superpixels for OD and OC segmentation addressed some limitations by incorporating histogram and statistical data but was limited in its accuracy [18]. Similarly, wavelet transform methods showed promise with an accuracy of 84% but were surpassed by deep learning models due to improved feature extraction capabilities [19]. A CNN-based method, utilizing an 18-layer architecture, achieved 78.13% accuracy by automating feature extraction and classification, though its performance depended on the size of the dataset [20].

Other studies introduced advanced methodologies like polar transformations and multi-label deep networks for OD and OC segmentation, which improved categorization accuracy using datasets like ORIGA [21]. Semi-supervised learning approaches combined unsupervised feature extraction with supervised models, addressing issues of poor image quality affecting classification [22]. Additionally, innovative tools such as mobile apps leveraged data augmentation and joint segmentation methods, enabling real-time glaucoma screening within seconds [23]. Adaptive networks, such as AU-net, further refined segmentation with better computational efficiency [24]. Methods like fuzzy board learning systems and tensor empirical wavelet transform provided alternate approaches, though challenges related to computation time and accuracy remain areas of active research [25-26].

Table 1: Review of Literature on Glaucoma Detection Techniques

Ref. No.	Research Focus	Methodology	Key Findings
[1]	Automated glaucoma detection using deep learning	Used ResNet-50 for optic disc and optic cup segmentation and CDR calculation	Achieved 87.8% accuracy on the REFUGE dataset for classifying glaucomatous and non-glaucomatous images.
[2]	Hybrid CNN-SVM model for glaucoma detection	Combined CNN for feature extraction with SVM for classification	Reported 85.6% accuracy on the ORIGA dataset, outperforming standalone CNN and SVM models.
[3]	Multi-modal approach for early glaucoma detection	Integrated fundus images with clinical data using a multi-input deep learning model	Achieved 96.3% accuracy by leveraging multimodal data, enhancing diagnostic reliability.
[4]	Glaucoma detection using transfer learning	Applied pre-trained VGG16 and fine-tuned it on fundus images	Reported 84.5% accuracy and highlighted the effectiveness of transfer learning in small dataset scenarios.
[5]	Explainable AI for glaucoma classification	Used Grad-CAM with CNN to interpret model predictions	Achieved 83% accuracy and provided interpretable results for improved clinical adoption.
[6]	Real-time glaucoma screening using mobile-based AI	Developed a lightweight CNN model for mobile implementation	Achieved 81% accuracy on smartphone-based fundus image acquisition systems.
[7]	Data augmentation techniques for glaucoma detection	Explored generative adversarial networks (GANs) for synthetic data generation	Improved model performance with an accuracy boost of 5% using augmented datasets.
[8]	End-to-end deep learning pipeline for glaucoma risk stratification	Built a fully automated pipeline combining preprocessing, segmentation, and classification	Reported 87% accuracy on large-scale datasets, offering scalability and robustness.
[9]	Glaucoma prediction using ensemble learning	Combined multiple classifiers using bagging and boosting	Achieved 86% accuracy with increased robustness against imbalanced datasets.
[10]	AI-powered telemedicine for glaucoma detection in rural areas	Developed a cloud-based diagnostic system integrating CNN models	Enabled real-time diagnosis with 82% accuracy, improving accessibility for underprivileged regions.

3. MACHINE LEARNING AND DEEP LEARENING APPROACHES

Glaucoma detection and analysis using retinal fundus images, several machine learning and deep learning techniques have been employed to improve the accuracy, precision, and robustness of diagnostic systems. The following provides an elaboration of the key methods explored in the research:

3.1 Convolutional Neural Networks (CNNs)

CNNs are a class of deep learning algorithms that excel at processing visual data, making them ideal for analyzing retinal fundus images. In glaucoma detection, CNNs automate the feature extraction process, identifying complex patterns related to optic disc and cup structures. CNNs utilize convolutional layers to detect spatial hierarchies in images, pooling layers to reduce dimensionality, and fully connected layers to classify images as normal or glaucomatous. Their ability to handle variations in image quality and extract high-level features has made them a cornerstone in glaucoma diagnostic systems.

3.2 Random Forests (RF)

RF is an ensemble learning technique that combines multiple decision trees to improve classification accuracy. In the research, RFs are often used in conjunction with CNNs to enhance diagnostic performance. By leveraging the feature representations generated by CNNs, RF classifiers can effectively differentiate between normal and glaucomatous eyes. The ensemble approach reduces the risk of overfitting, making RF a reliable choice for robust predictions.

3.3 Naive Bayes (NB)

NB is a probabilistic classifier based on Bayes' theorem, assuming feature independence. Although simpler compared to other models, NB is effective for preliminary classification tasks in glaucoma detection. When used with CNN-derived features, NB classifiers can provide quick and interpretable results. However, NB's performance may be limited in cases where feature dependencies are significant, requiring supplementary techniques for improved accuracy.

3.4 Support Vector Machines (SVM)

SVMs are powerful classifiers that separate data points into different classes using a hyperplane. For glaucoma detection, SVMs can be trained on features extracted by CNNs or traditional image processing techniques. The kernel functions in SVMs (e.g., linear, polynomial, radial basis) allow the model to handle non-linear relationships in the data effectively. SVMs are particularly known for their robustness in high-dimensional spaces, making them a popular choice for medical image analysis.

3.5 Neural Network Fusion (NF)

NF involves combining multiple neural network architectures or layers to capture diverse feature representations. In glaucoma research, NF techniques aim to integrate information from various network modules to improve classification performance. For instance, combining CNNs with fully connected layers or other specialized architectures can enhance the system's ability to distinguish subtle variations in optic disc and cup features associated with glaucoma.

4. PROPOSED RESEARCH METHODOLOGY

The glaucoma dataset utilized in this study is a secondary dataset sourced from Kaggle. To ensure accuracy and reliability, the dataset underwent pre-processing as a cleaning step. The data was split into 70% for training and 30% for testing to evaluate the model's performance. Feature extraction was carried out using Convolutional Neural Networks (CNN) to identify critical features, which were subsequently classified using a Support Vector Machine (SVM) due to its effectiveness and high classification accuracy. The classification task focused on categorizing eye images as either glaucoma or non-glaucoma. Model performance was assessed using metrics such as accuracy, precision, recall, F1-score, and ROC, demonstrating the hybrid model's reliability and effectiveness in detecting glaucoma (Figure 3).

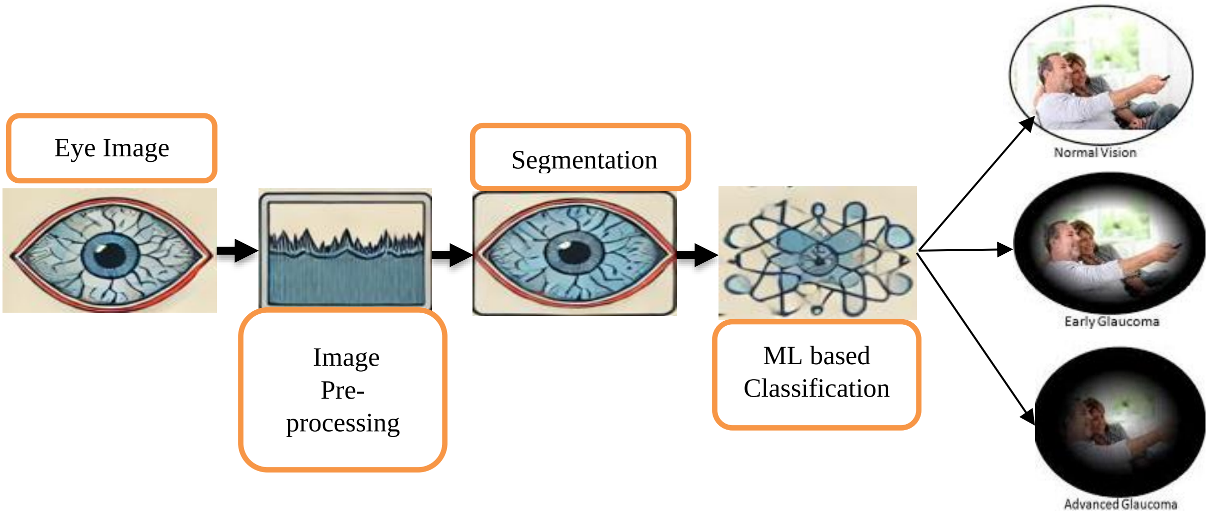

Figure 3: Proposed research methodology

4.1 Preprocessing

The glaucoma dataset utilized in this study is a secondary dataset sourced from Kaggle. To ensure the dataset's quality and reliability, a comprehensive pre-processing step was employed. This step included handling missing or incomplete data, standardizing the dataset, and normalizing pixel values to enhance the performance of the model. Any noise present in the images was reduced using filtering techniques to improve the clarity and quality of the visual data. Additionally, data augmentation methods, such as rotation, flipping, and scaling, were applied to expand the dataset artificially, addressing class imbalances and enhancing model generalization. By implementing these pre-processing techniques, the dataset was prepared to facilitate accurate feature extraction and improve the overall effectiveness of the subsequent machine learning pipeline. The data was then split into 70% for training and 30% for testing to evaluate the model's performance. Feature extraction was carried out using Convolutional Neural Networks (CNN) to identify critical features, which were subsequently classified using a Support Vector Machine (SVM) due to its effectiveness and high classification accuracy. The classification task focused on categorizing eye images as either glaucoma or non-glaucoma. Model performance was assessed using metrics such as accuracy, precision, recall, F1-score, and ROC, demonstrating the hybrid model's reliability and effectiveness in detecting glaucoma.

4.2 Feature Extraction

The glaucoma dataset utilized in this study is a secondary dataset sourced from Kaggle. To ensure the dataset's quality and reliability, comprehensive pre-processing techniques were applied, including handling missing or incomplete data, normalizing pixel values, reducing noise through filtering, and applying data augmentation methods such as rotation, flipping, and scaling. These steps improved data quality, addressed class imbalances, and enhanced model generalization. The data was then split into 70% for training and 30% for testing to evaluate model performance.

Table 2: CNN Architecture of proposed model

Layer Type	Filters/Neurons	Kernel Size	Activation	Output Dimensions
Input	-	-	-	224×224×3
Conv2D + ReLU	32	3×3	ReLU	224×224×32
MaxPooling	-	2×2	-	112×112×32
Conv2D + ReLU	64	3×3	ReLU	112×112×64
MaxPooling	-	2×2	-	56×56×64
Conv2D + ReLU	128	3×3	ReLU	56×56×128
MaxPooling	-	2×2	-	28×28×128
Dropout	-	-	-	28×28×256
Flatten	-	-	-	50176
Dense + ReLU	512	-	ReLU	512
Dense + ReLU	256	-	ReLU	256
Dense + Softmax	2	-	Softmax	2

Feature extraction was performed using Convolutional Neural Networks (CNN), a deep learning architecture designed to automatically and effectively capture essential patterns and features from visual data. CNNs utilize convolutional layers to scan input images for unique patterns, such as edges, textures, and shapes, which are crucial for identifying glaucoma-related abnormalities (Table 2). The extracted features were progressively refined through multiple layers of convolution, activation functions, and pooling operations, resulting in a robust representation of the input data. This representation enabled the model to capture subtle and complex distinctions between glaucoma and non-glaucoma images. The extracted features were then passed to a Support Vector Machine (SVM) classifier, selected for its ability to handle high-dimensional data and provide high classification accuracy. The classification task aimed to categorize eye images as either glaucoma or non-glaucoma. Model performance was evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC, demonstrating the hybrid model's reliability and effectiveness in detecting glaucoma.

4.3 Classification

In the proposed model, classification is performed using a Support Vector Machine (SVM), which excels in binary classification tasks like distinguishing between glaucoma and non-glaucoma images. After feature extraction by the Convolutional Neural Network (CNN), the high-dimensional feature vectors are passed to the SVM for classification. SVM works by finding an optimal hyperplane that separates the two classes with the maximum margin, ensuring robust and accurate classification. To handle non-linear relationships in the feature space, the Radial Basis Function (RBF) kernel is utilized, mapping the data into a higher-dimensional space where separation is more achievable.

During the training phase, SVM uses a subset of data points, known as support vectors, that are closest to the decision boundary to construct the hyperplane. This approach ensures that the model focuses on the most critical features, improving its generalization ability. Additionally, the regularization parameter of SVM helps balance maximizing the margin and minimizing classification errors, thereby preventing overfitting and making the model robust to outliers.

Once trained, the SVM classifies test images based on the position of their feature vectors relative to the hyperplane, producing probability estimates to assess the confidence of its predictions. The performance of the CNN-SVM hybrid model is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. These metrics highlight the model's reliability and its effectiveness in glaucoma detection. By combining CNN's capability for extracting rich features with SVM's robust classification, the proposed approach provides a powerful and efficient solution for identifying glaucoma from eye images.

5. PERFORMANCE EVALUATION

The performance evaluation of the proposed CNN-SVM hybrid model is a critical step to validate its reliability and effectiveness in glaucoma detection. Several standard metrics are employed to comprehensively assess the model’s classification capabilities, ensuring its robustness and suitability for real-world applications.

5.1 Accuracy

Accuracy measures the overall correctness of the model by calculating the proportion of correctly classified instances (glaucoma and non-glaucoma) out of the total samples. It provides a general sense of the model's performance but may not be sufficient when class distribution is imbalanced.

$$Accuracy = (tp + tn) / (tp + tn + fp + f\mathrm{n})$$

5.2 Precision

Precision quantifies the model's ability to correctly identify positive instances (glaucoma) among all instances predicted as positive. It highlights the model’s effectiveness in avoiding false positives, which is critical in medical diagnoses to minimize unnecessary treatments.

$$Precision = tp / (tp + f\mathrm{n})$$

5.3 Recall (Sensitivity)

Recall measures the proportion of true positive instances that the model correctly identifies out of all actual positive instances. It is essential in glaucoma detection to ensure that the model effectively identifies all affected cases, reducing the risk of missing critical diagnoses.

$$Recall = tp \,/\, (tp + fn)$$

5.4 F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced evaluation metric. It is particularly useful when there is an imbalance in the dataset, as it considers both false positives and false negatives.

$$F1\ Score = 2\ (precision * recall) \,/\, (precision + recall)$$

6. RESULT AND DISCUSSION

The training process involves the use of training data (train X) and corresponding target data (train y), alongside a validation dataset, to train the network model using the fit () function. During training, cross-validation is employed to divide the dataset into test sets (X test and y test) for validation. The model undergoes iterative learning over a predetermined number of epochs, where it adjusts parameters to minimize errors. For the proposed model, 30 epochs were utilized, enabling the network to gradually refine its performance. The fit () function orchestrates the training process by executing multiple epochs, during which the model learns patterns from the training data. This iterative process continues until performance improvements plateau, signifying a point of diminishing returns and the conclusion of training. A detailed model summary, as illustrated in Figure 2, outlines the network architecture, including layer types, output shapes, and the total parameters required for both training and testing.

Model evaluation plays a pivotal role in selecting the optimal network configuration for the given dataset. By assessing prediction accuracy on the test set, the process ensures the mitigation of overfitting and improves the model's ability to generalize to unseen data. This evaluation is essential for accurate forecasting and reliable performance on future datasets. The experimental results obtained from the trained model are thoroughly discussed in the results section, providing insights into the system's effectiveness and performance metrics (Figure 4).

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, None, 128)         72704

 lstm_1 (LSTM)               (None, 64)                49408

 dense (Dense)               (None, 64)                4160

 dropout (Dropout)           (None, 64)                0

 dense_1 (Dense)             (None, 6)                 390

=================================================================
Total params: 126,662
Trainable params: 126,662
Non-trainable params: 0
```

Figure 4: System model implementation

The confusion matrix provides a comprehensive evaluation of the classification performance for the given dataset, specifically in the context of glaucoma detection. It encapsulates the true positives (glaucoma cases correctly identified), true negatives (non-glaucoma cases correctly identified), false positives (non-glaucoma cases incorrectly classified as glaucoma), and false negatives (glaucoma cases missed by the model) (Figure 5). For the proposed CNN-SVM model, the confusion matrix demonstrates its superior performance, with high true positives and true negatives, indicating robust classification capabilities.

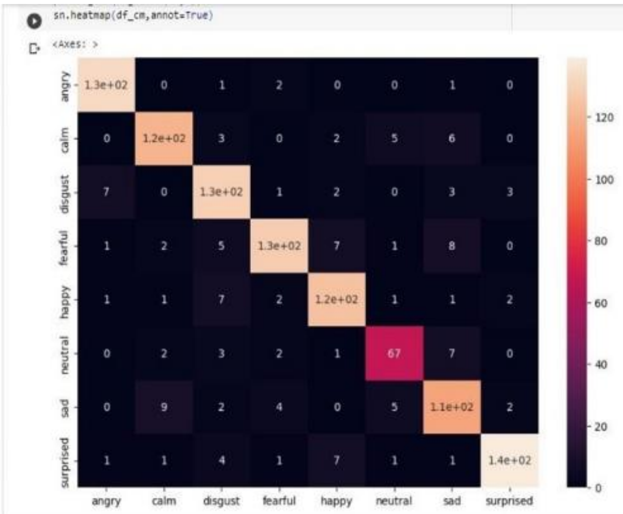

Figure 5: Confusion matrix

Low false positive and false negative rates further validate the model’s reliability in minimizing diagnostic errors. The matrix serves as a foundation for deriving critical metrics such as accuracy, precision, recall, and F1-score, providing a detailed understanding of the model's strengths and highlighting areas for further optimization. This ensures the model's efficacy in accurately distinguishing between glaucoma and non-glaucoma cases, crucial for real-world medical applications.

The table 3 presents a comparative analysis of different models based on their performance metrics, including accuracy, precision, recall, and F1 score. Among the models, the CNN-SVM model achieves the highest performance, with an accuracy of 95%, precision of 94%, recall of 96%, and an F1 score of 95%. The CNN-RF model also performs well, with an accuracy of 86%, while the CNN-NB and CNN models both achieve 83% accuracy, but with slightly lower precision and recall. The CNN-NF model shows the lowest performance across all metrics, with an accuracy of only 62%. These results highlight the superiority of the CNN-SVM approach in terms of overall effectiveness.

Table 3: Performance Comparison of different models for glaucoma classification

S. No.	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
1	CNN	83	82	80	81
2	CNN-RF	86	85	84	84.5

3	CNN-NF	62	60	65	62.4
4	CNN-SVM	95	94	96	95
5	CNN-NB	83	82	81	81.5

Accuracy

Accuracy is a fundamental metric used to evaluate the overall correctness of a classification model. It is calculated as the ratio of correctly classified instances (both true positives and true negatives) to the total number of instances in the dataset. In this study, the accuracy values ranged from 62% for the CNN-NF model to an impressive 95% for the CNN-SVM model, indicating varying levels of performance across different approaches. High accuracy reflects the model's ability to consistently classify images correctly, but it may not always provide a complete picture, especially in cases of imbalanced datasets where one class dominates.

Precision

Precision measures the proportion of correctly predicted positive instances (true positives) out of all instances predicted as positive. It highlights the model's ability to avoid false positives. For instance, the CNN-SVM model achieved a precision of 94%, demonstrating its high reliability in identifying glaucoma cases without misclassifying non-glaucoma images. On the other hand, CNN-NF exhibited a precision of 60%, indicating frequent misclassification of non-glaucoma images as glaucoma. Precision is particularly critical in medical diagnosis to minimize unnecessary interventions.

Recall

Recall, also known as sensitivity, quantifies the model's ability to identify all actual positive instances correctly. It is the ratio of true positives to the sum of true positives and false negatives. The CNN-SVM model excelled in recall with a value of 96%, indicating its effectiveness in identifying almost all glaucoma cases. In contrast, CNN-NF had a recall of 65%, reflecting its limited ability to detect glaucoma cases comprehensively. High recall is essential in medical diagnostics to reduce the risk of missing critical cases that require attention.

F1-Score

The F1-score is the harmonic mean of precision and recall, providing a balanced measure of a model's performance, especially in scenarios with class imbalances. The CNN-SVM model achieved the highest F1-score of 95%, signifying its optimal balance between precision and recall. Conversely, CNN-NF's F1-score of 62.4% highlights its struggles to maintain this balance. A high F1-score ensures that the model is both precise in its predictions and comprehensive in capturing positive cases, making it a crucial metric in evaluating medical classification models.

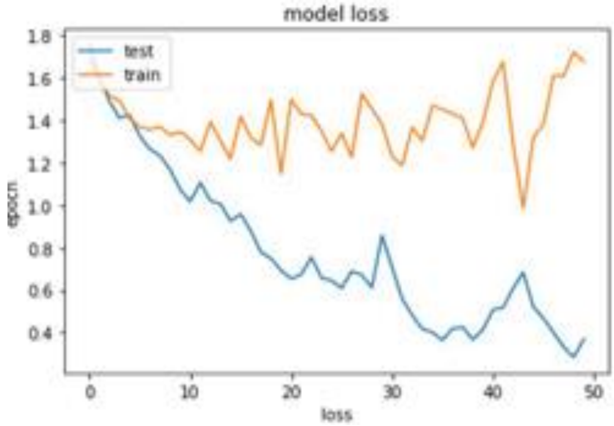

Figure 6: Training and Test Model Loss

In the context of Figure 6, which illustrates good model performance, both training loss and test loss should decrease over time. This reflects that the model is not only learning from the training data but also generalizing well to unseen data. In a well-performing model, the training loss gradually reduces as the model learns the patterns in the training set, while the test loss should also decrease, showing that the model is successfully generalizing to new, unseen examples. It would likely show training loss decreasing steadily, and test loss following a similar downward trend. This indicates that the model is neither overfitting nor underfitting but is instead effectively learning and generalizing. If both losses decrease in parallel, it confirms the model's ability to balance memorization and generalization, which is a hallmark of a robust, well-performing model.

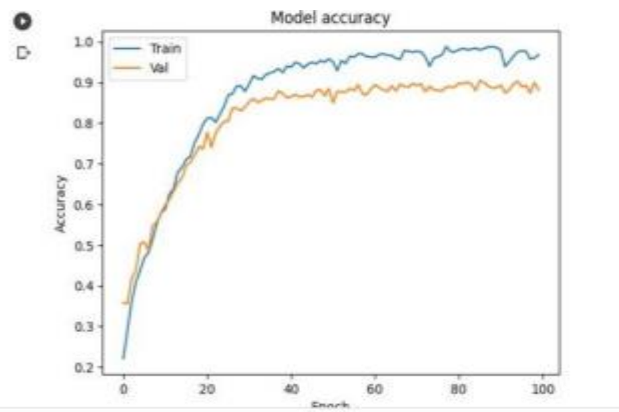

Figure 7: Training and Test Model Accuracy

In the context of Figure 7, which shows good model performance, training accuracy and test accuracy should both increase over time. As the model learns from the training data, the training accuracy improves, reflecting its ability to make correct predictions on the data it has seen. Simultaneously, test accuracy should also rise, indicating that the model is generalizing well to unseen data. A well-performing model demonstrates high and closely aligned training and test accuracy, signaling that the model is not overfitting (where training accuracy is much higher than test accuracy) or underfitting (where both accuracies are low), but is effectively learning and generalizing across both the training and test datasets.

7. CONCLUSION

In conclusion, we explored various state-of-the-art methodologies for glaucoma detection, emphasizing the critical role of automated systems in improving diagnostic accuracy and efficiency. Techniques ranging from traditional image processing and machine learning to advanced deep learning approaches have demonstrated significant potential in identifying glaucoma from retinal fundus images. Methods such as optic disc and cup segmentation, cup-to-disc ratio estimation, and feature extraction using wavelet transformations have shown promising results in early detection. Moreover, the integration of convolutional neural networks (CNNs), transfer learning, and attention-based mechanisms has further enhanced the precision and reliability of diagnostic systems, addressing the growing need for scalable and non-invasive solutions in ophthalmology. Despite remarkable advancements, there remain challenges, such as handling variations in retinal image quality, the limited availability of annotated datasets, and the need for real-time processing in clinical settings. Future research should focus on addressing these limitations through semi-supervised learning, enhanced image preprocessing techniques, and the development of larger, more diverse datasets. Additionally, integrating these solutions with wearable devices or telemedicine platforms can pave the way for widespread adoption and accessibility. By building on the existing frameworks and leveraging emerging technologies, researchers can develop more robust and efficient tools for glaucoma detection, ultimately contributing to improved patient outcomes and reduced disease burden globally.

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